





## Where Are the Poor Located? A Spatial Heterogeneity Analysis of Monetary Poverty in Peru

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### Abstract

Measuring poverty is a first step to the design of effective public policies, however, it is also essential to know where the poor are located. The main objective of this research is to evaluate the spatial heterogeneity of the factors that influence monetary poverty for each district in Peru. We apply a Geographically Weighted Regression (GWR) approach, which allows us to capture the non-stationarity of the hidden data and to provide coefficients for each district, unlike the OLS model. This research mainly uses the Poverty Map and the Population and Household Census of Peru, both from 2007 and 2017. The overriding findings of our results indicate that female headship, secondary education, electricity, and sanitation services are directly associated with poverty reduction at the local level. For 2007, significant effects are mainly concentrated in the districts of Pasco, Lima and Cajamarca regions. For 2017, the results show a shift towards districts of Junín, Huancavelica, and Cajamarca regions. Likewise, it is highlighted that the highest mean negative effect on poverty is generated by Secondary Education in the GWR estimates; while malnutrition represents the highest mean positive effect on poverty for the level and intercensal models. Finally, the empirical evidence found in this research can help establish better policy designs at the district level.

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## 1. Introduction

Most researchers have carried out systematic and detailed studies about poverty measurements, the evolution of poverty dynamics, the mechanisms that cause poverty and strategies to reduce poverty (Escobal et al., 1999; Herrera and Cozzubo, 2016; Verdera, 2007). Nevertheless, little attention has been paid to the socioeconomic accessibility factors that explain the spatial heterogeneity of poverty in Peru at different territorial levels (Li et al., 2020). In this case, the spatial heterogeneity refers to the fact that the poor population is located and assembled in specific geographical areas. Therefore, determining the spatial heterogeneity of poverty is one of the issues that has generated most concern in the field of public policies in different countries.

For that reason, one of the tools that makes possible to spatially represent diverse economic, social and environmental characteristics of a country at any administrative territorial level is the Poverty Map. It gives out information to capture the existent heterogeneity of poverty and identify clusters to design social policies and prioritize the scope of intervention at the local level. In Peru, the National Institute of Statistics and Informatics (known as INEI by its initials in Spanish) elaborates the poverty map based on a monetary approach. It should be noted that monetary poverty indicator is the official measure in Peru and the main indicator of this study, despite its limitations with respect to other approaches such as multidimensional poverty (Clausen and Flor, 2014). The monetary poor population is defined by INEI as those who reside in households whose per capita outlay is not enough to acquire a basic food basket and non-food items (housing, clothing, education, health, transportation, etc.).

According to INEI estimates, Peru has achieved considerable success in reducing monetary poverty over the last 15 years, denominating this period as pro-poor because poor population has decreased from 58.7% for 2004 to 20.2% for 2019, in a context of high economic growth for the country (Cord et al., 2015; Aldana et al., 2019). Though this systematic decrease in national poverty, high rates of poverty in rural areas still persist, with a value of 40.8% in 2019, 20 percentage points higher than the national level, representing an outstanding challenge for public policies designed to rural context. To highlight this point, the increasing complexity of the poverty problem emphasizes the importance of conducting poverty research at a local level to achieve targeted policy implementation and enhance the effects of poverty reduction (Li et al., 2020).

The measurement of poverty is a fundamental first stage to the design of effective social policies. However, a second stage is to identify where the poor are really located in the Peruvian territory. Thus, the main objective of this research is twofold. First, we evaluate the main factors that influence over the spatial heterogeneity of monetary poverty using a Geographically Weighted Regression (GWR) model. Second, we try to contribute to the literature by providing territorial policy recommendations to address poverty in the different districts. To our knowledge this is the first time that spatial heterogeneity of monetary poverty has been evaluated for Peru. Moreover, the main advantages of this econometric approach is to capture the spatial variability of the data and to provide estimates for each territorial administrative level, in contrast to an OLS model, whose factors are constant in all districts. We use data from the 2007 and 2017 Poverty Maps and Population and Household Census of Peru to estimate two level models corresponding

to both years and an inter-census model, considering variables related to education, work, health, among others.

The results of this research allow us to identify the districts with significant local coefficients of the different socioeconomic variables on poverty. On the one hand, the increase in secondary education, electricity, sanitation services or female headship has an effect on poverty reduction, predominantly in districts of the regions of Pasco (central highlands), Lima (central coast) and Cajamarca (north) for 2007; while for 2017, this significant effect is registered in the regions of Junín, Huancavelica and Cajamarca. On the other hand, unemployment, malnutrition and altitude are factors that contribute to the increase in poverty in districts of the regions of Áncash (central coast), Arequipa and Ayacucho (south) for 2007; while for 2017, this effect is concentrated in the districts of the Cusco, Tacna and Áncash regions. In addition to these main findings, it is highlighted that the largest average negative effect on poverty is generated by secondary education in the GWR estimates; while malnutrition represents the largest average positive effect on poverty for both the level and intercensal models.

The document is structured as follows. Section 2 presents a brief empirical review. Section 3 explains the methodology of geographically weighted regressions. Section 4 shows the databases and describes statistics of the variables used for the study. Section 5 presents the results of the spatial patterns of poverty, as well as the estimates of the GWR model. Finally, Section 6 presents the conclusions and policy recommendations.

## 2. Literature Review

In most countries, poverty is closely related to the geographical environment (Jalan and Ravallion, 2002; Kraay and McKenzie, 2014). Researchers such as Xu et al. (2019); Qu et al. (2012); Olivia et al. (2011) confirm the hypothesis that the characteristics of the local natural environment, specifically geographic conditions, are strongly related to regional poverty. Additionally, Bird et al. (2011) mention that physical isolation contributes to the emergence of a spatial poverty trap; that physical isolation contributes to the emergence of a spatial poverty trap, usually found in remote geographic areas; fragile ecological environments; poor public infrastructure and politically disadvantaged areas.

In this section, the main factors that explain territorial poverty in the Peruvian context are reviewed. A first variable that has an effect on poverty is related to access to services. For example, having access to basic services such as electricity, sanitation, and drinking water is relevant to reduce the vulnerability of households in the economy. Reinikka and Svensson (1999) mention that housing infrastructure is the capital that provides the necessary support services to undertake private activities. Thus, a household that does not have access to drinking water, sewerage or electricity has no possibility of obtaining a better wellbeing and, therefore, its economic position is seriously affected. Among the studies that have analyzed access to basic services as a determinant of poverty in the Peruvian case, Escobal et al. (1999) found significant impacts of the drinking water, sewerage, electricity, and telephone service on poverty, highlighting that the lack of access to certain assets generates insufficient income flows to fight poverty. Moreover, Aparicio et al. (2011) have conducted a study where they conclude that

the probability of being poor fluctuates from 12%, when the household has water, sewerage, electricity and telephone access, to 45% when it does not have any of these four services.

Another determinant of poverty is education. [Becker \(1964\)](#) mentioned that investment in human capital is key to economic progress, both at the macro (country, region) and micro (individual) levels. In the Peruvian case, [Benavides \(2004\)](#) mentions that, although there are variable social conditions, education always increases the probability of social mobility and has an intergenerational role, that is, as parents become more educated, the educational level of the children will be higher, and therefore, they will be able to escape from poverty. [Ordaz \(2009\)](#) points out that, in the context of the rural sector in Mexico, a person with completed secondary education reduces, significantly, their probability of being in a situation of poverty, compared to a person with only a complete primary education, concluding that, a higher educational level represents an effective instrument for overcoming poverty.

Another relevant variable affecting poverty is chronic child malnutrition. According to the [World-Bank \(2006\)](#), malnutrition slows economic growth and perpetuates poverty through three pathways: (i) low productivity resulting from poor health status; (ii) impaired cognitive functions and lack of schooling; and (iii) increased health care costs. Likewise, this evidence converges towards the formation of a vicious cycle. For instance, child malnutrition has consequences in adulthood, generating a reduction in human capital and wages, associated with fewer years of education due to lower cognitive development, also generating limitations in productivity. These factors make it difficult to overcome poverty. In turn, these adults conform families whose children are at greater risk of being harmed by child malnutrition ([Segura et al., 2002](#)). In the Peruvian case, [Alcázar et al. \(2013\)](#) show that the greatest costs generated by malnutrition come mainly from lost productivity; the authors also point out that malnutrition affects the highland and jungle regions of Peru.

The results of the various studies on poverty and gender analysis in household headship are mixed. On the one hand, we have studies that conclude that female headship in the household exacerbates poverty, due to their disadvantage in economic participation, wage gap, discrimination, domestic work, educational level, among others ([Moghadam, 1997](#); [Kabeer, 2003](#); [Mahoozi, 2015](#); [Paes de Barros et al., 2006](#)). In contrast, authors such as [Cortés \(1997\)](#) show that poverty is lower in households headed by women, due to the efficiency of household management. Likewise, in-depth studies on the situation of the children of female-headed households show better levels of nutrition, health and education ([Blumberg, 1995](#); [Oppong, 1997](#)). Finally, according to [Chant \(2003\)](#), the debates on female headship of household and poverty have brought into discussion the issue of “empowerment of women”, which emphasizes that the ability to control and allocate resources in the household is as important as the power to obtain those resources.

Regarding unemployment, the study by [Saunders \(2002\)](#) finds that the prolongation of unemployment increases the probability of a household falling into poverty. That is, 13% of poor people in Australia registered being unemployed for eight weeks, while 80% of the poor registered being unemployed for more than a year. In the Peruvian case, [Yamada and Montero \(2008\)](#) find not only a significant impact of unemployment on the poverty level of the general population, but also which groups are the most vulnerable. Indeed, they find that the incidence of falling

into poverty is higher when household head is unemployed than when a spouse or another member of the household is unemployed. Likewise, they find a higher incidence of poverty when the unemployed household member is a woman.

From this brief literature review, it is inferred that the problem of poverty in Peru not only is related to the social and economic aspects, but also leads to strategies that relate poverty to the geographical location, the environment, and socioeconomic characteristics of a given region. Hence, the increasing complexity of the poverty problem highlights the importance of conducting poverty research at a local level to achieve targeted policy implementation and enhance the effects of poverty reduction (Li et al., 2020).

### 3. Methodology

In a spatial analysis context, the link between dependent variable and independent variables varies with changes in geographical location. Such spatial variation is called spatial non-stationarity. However, the linear regression (OLS model) assumes that the effect of explanatory variables remains stable over the region and thus fails to reflect the spatial non-stationarity of different independent variables over the entire area. The equation form of the global regression model (OLS) is as follow:

$$y_i = \beta_0 + \sum_{k=1}^m \beta_k x_{ik} + \epsilon_i, \quad i = 1, 2, \dots, n, \quad (1)$$

where  $y_i$  is the dependent variable,  $x_{ik}$  is the value of the  $k$ -th independent variable and  $\epsilon_i$  is the error term. However, we apply the Geographically Weighted Regression (GWR), which allows regression coefficients to vary across space, thereby allowing parameter values to vary between locations (Fotheringham et al., 2003). The authors Brunsdon et al. (1996) introduced the GWR model in the spatial literature by proposing a variation to the linear regression model, which consists of adding information on geographical location to obtain local rather than global parameters. The GWR model is defined as follows:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{k=1}^m \beta_k(\mu_i, \nu_i) x_{ik} + \epsilon_i, \quad i = 1, 2, \dots, n, \quad (2)$$

where  $(\mu_i, \nu_i)$  represent the spatial coordinates (latitude, longitude) of the  $i$ -th sample point, and  $\beta_k(\mu_i, \nu_i)$  states the value of the continuous function  $\beta_k(\mu, \nu)$  of the  $i$ -th location. If  $\beta_k(\mu, \nu)$  does not vary in space, GWR becomes a global model (OLS). The GWR model is based on the non-parametric locally weighted regression technique where the regression parameters are estimated using data subsets that are close to the model's estimation location in a geographic space (Wheeler and Páez, 2010). These parameters are estimated using a weighting function based on the distance of the geographic coordinates of the data, that is, those variables that are closest to the estimation point will have a greater influence on the estimation. The GWR parameter estimates at location  $i$  are solved using the following equation, given in matrix form:

$$\widehat{\beta}(\mu_i, \nu_i) = [X'W(\mu_i, \nu_i)X]^{-1}X'W(\mu_i, \nu_i)Y, \quad (3)$$

where  $\widehat{\beta}_i$  is the vector of local regression coefficients at location  $i$ ;  $Y$  is the  $n \times 1$  vector of dependent variables;  $X$  is the matrix of independent variables, which includes a leading column of ones for the intercept; and  $W_i$  is the  $n \times n$  spatial weighting matrix whose diagonal elements denote the geographical weighting for each data at location  $i$  (Fotheringham et al., 2001):

$$W(\mu_i, \nu_i) = \begin{pmatrix} w(d_{i1}) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & w(d_{in}) \end{pmatrix}_{N \times N}. \quad (4)$$

The spatial weighting matrix,  $W(\mu_i, \nu_i)$ , is calculated using a Kernel function that calculates the weights of the observations inversely related to the distance, that is, it assigns more weight to the data that are closest to the estimation point as opposed to those that are further away. The function commonly used to calculate the spatial weights that monotonically decrease with distance is the Gaussian kernel function (Wheeler and Páez, 2010; Leung et al., 2000):

$$w_{ij} = \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{\delta}\right)^2\right), \quad (5)$$

where  $d_{ij}$  is the distance between observations  $i$  and  $j$ , and  $\delta$  is the kernel bandwidth parameter. The weight ( $w_{ij}$ ) for observation  $j$  relative to observation  $i$  change as a function of the distance ( $d_{ij}$ ) and the kernel bandwidth ( $\delta$ ) controls the range and decay of spatial correlation (Wheeler and Páez, 2010). The weighting through the Kernel function responds to the assumption of spatial autocorrelation that if it is fulfilled, non-stationary patterns will be obtained in the estimated coefficients (Wheeler and Páez, 2010; Páez et al., 2002).

According to the literature, there are two types of Kernels for using in GWR models: adaptive and fixed Kernel functions. We use the adaptive kernel because it adjusts to the density of the data by varying the bandwidth, which is the inverse of density. This allows flexibility to reduce the variance of the estimates in areas with few observations and reducing the bias of the estimates in areas with many observations (Van Kerm, 2003; Bowman and Azzalini, 1997; Pagan and Ullah, 1999). Moreover, adaptive Kernel function estimates are obtained through optimization methods such as Cross Validation (CV), Generalized Cross Validation (GCV), Akaike information criteria (AIC), Akaike information criteria corrected ( $AIC_c$ ) (Brunsdon et al., 1996; Cleveland, 1979; Van Kerm, 2003; Farber and Páez, 2007; Wheeler and Páez, 2010). We use the procedure  $AIC_c$  to estimate the bandwidth, and its formula is the follow:

$$AIC_c = 2n [\ln(\widehat{\sigma})] + n [\ln(2\pi)] + n \left[ \frac{n + \text{tr}(P)}{n - 2 - \text{tr}(P)} \right], \quad (6)$$

where  $\widehat{\sigma}$  is the maximum likelihood estimator and  $\text{tr}(P)$  is the trace of the projection matrix of the GWR model. It should be noted that the lowest value of  $AIC_c$  is the best model. Moreover, this criterion allows to compare the degree of adjustment of the GWR estimate with respect to that obtained by OLS.

In addition to the standard GWR model, there is an extension called the Mixed Geographically Weighted Regression (MGWR) model (Mei et al., 2004). It assumes that not all coefficients are variable, that is, there are mixed coefficients in the model: local and global. The model is defined

as follow:

$$y_i = \sum_{l=1}^p \beta_l x_{il} + \sum_{j=1}^k \beta_j (\mu_i, \nu_i) x_{ij} + \epsilon_i, \quad i = 1, 2, \dots, n, \quad (7)$$

where  $\beta_l$  ( $l = 1, \dots, p$ ) are fixed or global coefficients, and remaining coefficients vary according to their geographical location, as shown in equation (2). To determine the application between MGWR or GWR, Monte Carlo simulation was used, which sequentially compares the spatial variability of each coefficient.<sup>1</sup> The advantage of the mixed coefficient model consists in identifying variables that are not affected by the local context and, therefore, detects those factors with a homogeneous impact on the phenomenon to be explained, regardless of their geographical location.

#### 4. Data and Variables

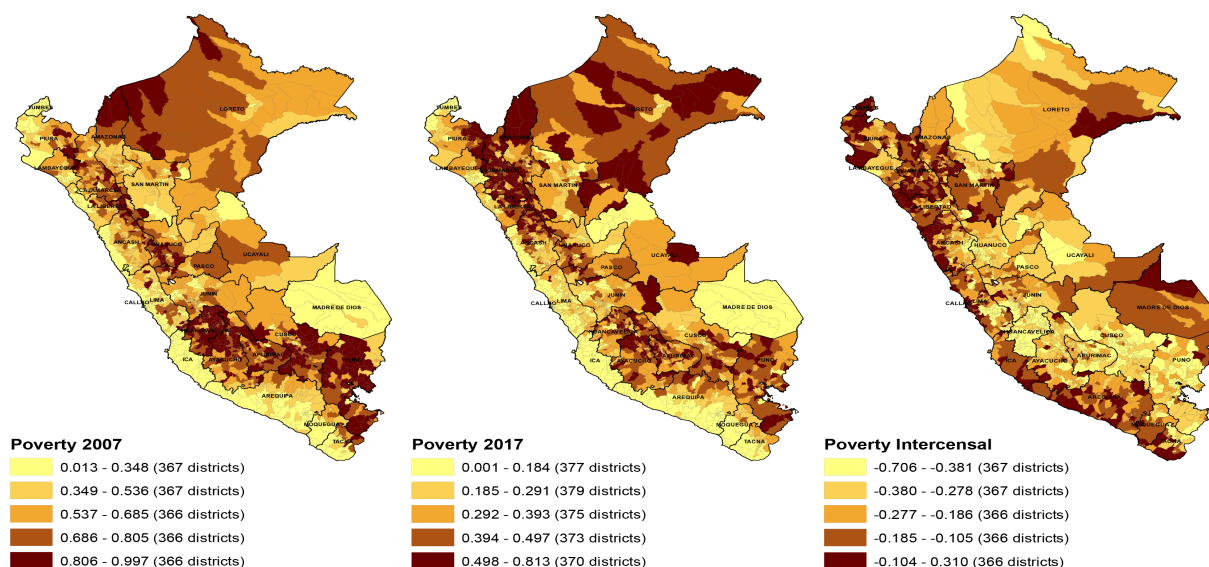
This study mainly uses data from the Poverty Map and the Population and Household Census, both for the years 2007 and 2017, made available by INEI. First, the Poverty Map provides information on disaggregated poverty rate at the level of each district in Peru. It is important to mention that this poverty rate is calculated using small area estimates in order to obtain reliable data at district level.<sup>2</sup> Figure 1 shows the geographical distribution of monetary poverty at district level for both years, 2007 and 2017, and the intercensal change. As can be seen, in 2007, high poverty rates were mainly concentrated in the southern highlands of Peru (Huancavelica, Apurímac and Puno). Unlike 2007, poverty rates in 2017 are concentrated in the northern highlands (Cajamarca and La Libertad) and the jungle (Amazonas and Loreto). As we move towards more densely populated districts on the coast, the numbers decrease, reaching rates of 13% in 2007 and 1% in 2017.

Second, the Population and Household Census is designed to capture the socioeconomic development and economic well-being of Peruvian households and individuals, covering multiple dimensions such as educational level, family relationships, housing infrastructure and economic activities. Censuses in Peru are conducted approximately every 10 years. Additionally, an important aspect to mention about both censuses is the difference in the number of districts, that is, the 2007 census has information from 1832 districts, while in the 2017 census this number increases to 1874 districts. Table 1 shows the descriptive statistics of the remaining variables obtained from the census for 2007, 2017 and the intercensal change.

Among the control variables, there are socioeconomical variables such as the percentage of female heads of households, with a rate of 26.5% in 2007 and 31.3% in 2017 by district. Another variable is the rate of individuals with completed secondary, whose percentage is 17.1% in 2007 and 23.3% in 2017. According to Benavides (2004), a low level of education (primary or secondary) is associated with a high rate of poverty. Hence, there is likely to be an inverse

<sup>1</sup>The Monte Carlo test runs once to derive the local parameter estimates and then repeatedly derives new local parameter estimates after randomly rearranging the data points to measure whether the variability of each parameter surface could have arisen by chance. For more details, see Li and Fotheringham (2020).

<sup>2</sup>This data can be downloaded for 2007 in [https://www.inei.gov.pe/media/MenuRecursivo/publicaciones\\_digitales/Est/Lib0911/index.htm](https://www.inei.gov.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib0911/index.htm), and for 2017 in <https://www.inei.gov.pe/cifras-de-pobreza/>.



Notes: The territory of Peru is divided into 24 regions. Own elaboration based on INEI.

**Figure 1.** Spatial distribution of poverty rate.

**Table 1**

Descriptive statistics of the variables.

Variables	2007 N=1832 observations				2017 N=1874 observations				Intercensal N=1832 observations			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Poverty (%)	0.581	0.229	0.013	0.997	0.341	0.169	0.001	0.813	-0.241	0.152	-0.706	0.310
Female Head (%)	0.265	0.073	0.073	0.502	0.313	0.076	0.099	0.525	0.049	0.047	-0.187	0.255
Secondary Education (%)	0.171	0.073	0.013	0.468	0.233	0.073	0.061	0.488	0.062	0.036	-0.112	0.239
Unemployment (%)	0.049	0.050	0	0.433	0.037	0.035	0	0.569	-0.012	0.054	-0.430	0.543
Electricity (%)	0.405	0.207	0	0.909	0.770	0.162	0	1	0.367	0.171	-0.506	0.907
Sanitation Services (%)	0.172	0.201	0	0.905	0.417	0.269	0	1	0.249	0.170	-0.433	0.917
Malnutrition (%)	0.385	0.179	0	0.996	0.211	0.116	0	0.833	-0.173	0.145	-0.761	0.390
Ln(Altitude)	7.095	1.609	1.099	8.476	7.139	1.493	1.609	8.456	0.049	0.242	-2.019	2.965

Note: Own elaboration based on data used in the estimations.

relationship between poverty and the average level education. Similarly, the percentage of unemployment is 4.9% per district in 2007, and 3.7% in 2017. A positive relationship between the rate of unemployment and poverty is expected (Yamada and Montero, 2008).

There is a group referencing to housing services such as electricity access and sanitation services. In this paper, access to housing services refers to the minimum requirements that housing must meet, such as access to electricity, which represents 40% on average per district in 2007, while in 2017 the figure rises to 77%. Likewise, sanitation services considers if housing is connected to a public sewage system inside or outside the home, which represents 17.2% in 2007, increasing to 41.7% in 2017. It should be noted that other variables such as water service or fuel used for cooking were constructed, but they were not considered in the research due to the high correlation with electricity access and sanitation services.



Likewise, chronic child malnutrition is still a problem that persists in Peru and not only has fatal consequences for those who suffer from it, but for society in general. In the short term, this public health problem causes a high rate of infant mortality (Aparicio et al., 2011). In the medium term, its consequences are seen to the detriment of the physical and cognitive development of minors. The results for chronic child malnutrition in 2007 is 38.5%, while in 2017 is 21.1%.

Further, Peru has a diversity of climates throughout its territory, ranging from the arid and warm coastal areas through the inter-Andean valleys of the temperate, frigid and polar type to those of the warm and rainy type of the jungle. Likewise, it is considered as highly vulnerable to climatic anomalies (MINAM, 2014). According to CAF (2014), Peru is one of the countries in South America that is classified in the “high risk” category of climatic vulnerability, while Paraguay and Bolivia are the only two countries classified as “extreme risk”, and Chile is the only country with a “low risk” classification. Thus, the microclimates and the high climatic vulnerability registered in Peru cause that some districts are more affected than others before the variability of the climate. For each year, the altitude of the districts is around 7.1% m.a.s.l. This variable is used in studies such as Escobal and Ponce (2016) for the case of Peru.

## 5. Empirical Results

This section explains the spatial relationship between the monetary poverty rate and the factors that influence this phenomenon using GWR.

### 5.1 Estimations

The empirical regression analysis begins with the application of a traditional OLS, whose results were standardized in order to compare the degree of impact of each variable on poverty. These results are presented in Table 2. Almost all variables have statistically significant coefficient and their signs are as expected. Besides, OLS model has high adjusted  $R^2$  value of 64.3% and 59.8% for 2007 and 2017, respectively. However, this value is reduced to 9.4% for the intercensal model, that is, the explanation for the variability of poverty is very low related to the previous models.

Moreover, Table 2 shows that, in the case of Malnutrition and Altitude, the coefficients are positive and significant at 1% in all estimates. Particularly, the positive and significant coefficient of Malnutrition obtained from the intercensal model means that the decreasing trend of Malnutrition from 2007 to 2017 is relatively important to explain also the reduction of poverty in that period.

The estimated coefficients for Sanitation Services and Secondary Education are significantly negative at 1% for the year 2007 and 2017, while for the model in differences, the coefficient has the same sign, but at a significant level at 5%. About this, although both variables have a lower level of significance in intercensal model, it is recognized that the increase of more people with secondary education and more households with sanitation services between 2007 and 2017 are important to explain the reduction in poverty. In the case of Unemployment, the

**Table 2**

Results of linear regression (OLS).

Dependent Variable: Poverty rate	2007	2017	Intercensal
Female Head (%)	0.035** (0.054)	-0.143*** (0.044)	0.043* (0.076)
Secondary Education (%)	-0.175*** (0.061)	-0.290*** (0.047)	-0.064** (0.106)
Unemployment (%)	0.100*** (0.065)	0.097*** (0.108)	0.032 (0.066)
Electricity (%)	-0.122*** (0.025)	-0.045** (0.023)	0.022 (0.022)
Sanitation services (%)	-0.220*** (0.024)	-0.273*** (0.013)	-0.053** (0.021)
Malnutrition (%)	0.332*** (0.029)	0.219*** (0.034)	0.244*** (0.025)
Ln(Altitude)	0.178*** (0.003)	0.242*** (0.002)	0.117*** (0.013)
Adjusted $R^2$	64.3	59.8	9.4
$AIC_c$	-2079.126	-3042.335	-1874.879
$z$ (Moran I residuals)	31.116***	32.513***	33.805***

*Note:* \*, \*\*, \*\*\* denote statistical significance at 10%, 5% and 1%, respectively. Robust standard errors in parentheses.

coefficients obtained are positive and significant at 1% on the poverty rate only for 2007 and 2017 estimates. Similar results are observed for Electricity, the coefficient in the intercensal model is not significant, while for 2007 and 2017, the coefficients are significant at 1% and 5%, respectively. Finally, in 2007, Female Head shows a positive and significant coefficient at 5%, whose magnitude is close to the value obtained in the intercensal model, whose significance level is 10%. In contrast to these results, in 2017, the coefficient is negative and significant at 1%, with a magnitude that quadruples the 2007 value.

In addition, to test the global spatial dependence in the OLS residual, we use Moran I test [Moran \(1950\)](#). This statistic captures the degree to which variables in one location are similar to those in neighboring locations. Using a contiguity matrix, [Table 2](#) presents significant  $z$  (Moran I residuals) values of spatial autocorrelation, which gives us the first clue of spatial dependence. However, Moran's I only detects global variation, therefore we explore local variation using the GWR model.

As stated above, GWR has the power to capture and examine the non-stationarity of hidden data by global model (OLS). This non-parametric technique allows obtaining coefficients that vary across the space, thus permitting a different set of coefficients to be obtained for each of the points that form the data. In addition, to obtain these results, a Monte Carlo was first tested to identify whether to use a MGWR or GWR model. The aim is to detect the presence of fixed variables in a mixed model, which can have a uniform impact on poverty, regardless of geographic location. However, as a result, all variables showed significant spatial variability implying local effects on poverty. The results of the GWR model are presented in [Table 3](#), where six statistical values are shown for each variable: mean, minimum, first quartile, median, third quartile and maximum for 2007, 2017 and intercensal.

**Table 3**

Results of GWR models.

**(a) Census 2007.**

Independent Variables	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum
Female Head (%)	-0.029	-1.279	-0.270	-0.066	0.189	1.182
Secondary Education (%)	-0.589	-2.305	-0.960	-0.523	-0.158	1.427
Unemployment (%)	0.098	-3.944	-0.113	0.117	0.336	2.782
Electricity (%)	-0.084	-0.530	-0.190	-0.077	0.024	0.564
Sanitation services (%)	-0.230	-0.752	-0.386	-0.216	-0.081	0.491
Malnutrition (%)	0.343	-0.480	0.089	0.303	0.494	1.550
Ln(Altitude)	0.097	-0.642	0.014	0.053	0.146	0.880
<b>Goodness of fit</b>	<b>Adjusted <math>R^2</math>: 83.9</b>			<b>AICc: -3181.9</b>		

**(b) Census 2017.**

Independent Variables	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum
Female Head (%)	-0.317	-1.189	-0.460	-0.313	-0.153	0.509
Secondary Education (%)	-0.359	-1.885	-0.589	-0.394	-0.140	0.632
Unemployment (%)	0.318	-2.213	0.030	0.242	0.607	3.719
Electricity (%)	-0.092	-0.433	-0.172	-0.088	-0.020	0.338
Sanitation services (%)	-0.156	-0.470	-0.217	-0.138	-0.089	0.087
Malnutrition (%)	0.295	-0.192	0.158	0.289	0.427	0.995
Ln(Altitude)	0.045	-0.448	0.012	0.041	0.082	0.317
<b>Goodness of fit</b>	<b>Adjusted <math>R^2</math>: 80.7</b>			<b>AICc: -4171.3</b>		

**(c) Intercensal.**

Independent Variables	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum
Female Head (%)	0.098	-0.924	-0.130	0.072	0.293	1.258
Secondary Education (%)	-0.117	-2.477	-0.368	0.035	0.304	1.388
Unemployment (%)	0.046	-1.431	-0.132	0.116	0.314	1.029
Electricity (%)	-0.076	-0.521	-0.134	-0.066	0.008	0.242
Sanitation services (%)	-0.014	-0.327	-0.095	-0.009	0.060	0.310
Malnutrition (%)	0.122	-0.496	0.032	0.152	0.274	0.652
Ln(Altitude)	0.108	-2.115	-0.033	0.047	0.185	0.3267
<b>Goodness of fit</b>	<b>Adjusted <math>R^2</math>: 50.7</b>			<b>AICc: -2786.7</b>		

Note: Own elaboration based on data used in the estimations.

On the one hand, it is highlighted that the highest negative mean effect on poverty is generated by Secondary Education for 2007, 2017 and intercensal, with mean values of  $-0.589$ ,  $-0.359$  and  $-0.117$ , respectively, the sign being stable with that obtained in the OLS. These results may be related to the fact that in recent years there have been positive changes in the completion of secondary education, particularly in historically disadvantaged areas. Likewise, the route for decentralized management established since 2002 is probably driving the favorable effect against poverty by adapting the educational offer to the heterogeneity of the national territory (Reátegui et al., 2017).

On the other hand, Malnutrition represents the largest mean positive effect on poverty for the model in levels and intercensal with mean values of  $0.343$ ,  $0.295$  and  $0.122$ , respectively, coinciding with the sign obtained in the OLS. In effect, Peru has made great progress in reducing

malnutrition not only in rural areas but also in urban areas in all regions. This improvement is possibly due to the high economic growth rates registered for more than a decade which, in addition to increasing household income, allowed the government to increase spending on social programs such as the *Juntos* program. According to [Sanchez et al. \(2016\)](#), exposure to the *Juntos* program during the first three years of life reduces by 13.4 percentage points the probability of suffering from severe stunting, decreasing the risks of deterioration of cognitive functions, low productivity and poverty.

In the case of Unemployment, the mean value in 2007 is 0.098, close to that obtained in the OLS; however, this mean value is reduced to almost half, 0.046, for the intercensal estimation. For both models, the local coefficients fluctuate between negative and positive values, but the latter predominating. A similar behavior is observed in 2017, whose mean value increases to 0.318, however the central local coefficients are concentrated in positive values fluctuating between 0.030 and 0.607. In relation to this, [Franco and Ñopo \(2018\)](#) report an important finding, in the period from 2006 and 2016, the authors evidenced that the proportion of poor young people who are part of the Employee Assistance Program (EAP) in Peru decreased by 10 percentage points. That is, young people are giving up the labor market, probably after failing to find any job or quality employment. This becomes a cause for concern, as according to the asset approach of the poor, part of the population in poverty can escape from poverty as long as their asset holdings vary, therefore, employment can be a source of income that would explain the exit from poverty or return to it, otherwise, according to [Escobal et al. \(1999\)](#).

In relation to the variables about household condition, the average values of the local coefficients of Electricity and Sanitation are negative for the three estimated models, and the values of the 25th and 75th percentiles are predominantly negative for these two variables, which means that this inverse effect on poverty occurs in most districts of Peru. These results are in accordance with that presented by [Aparicio et al. \(2011\)](#), who affirm that having access to electricity and sanitation is of the most importance to reduce the vulnerability of households. Moreover, [Fukusaki and Pérez \(2005\)](#) evaluated the National Fund for Compensation and Social Development (FONCODES) that finances drinking water, sewerage, latrine and electrification projects aimed at improving the quality of life of the poor population. One of its results is that electrification projects increased the value of homes and improved the well-being of families. Likewise, [Pastor \(2011\)](#) points out that there is progress in the management of sanitation in urban areas, where more than 60% of the provision of drinking water is under business control.

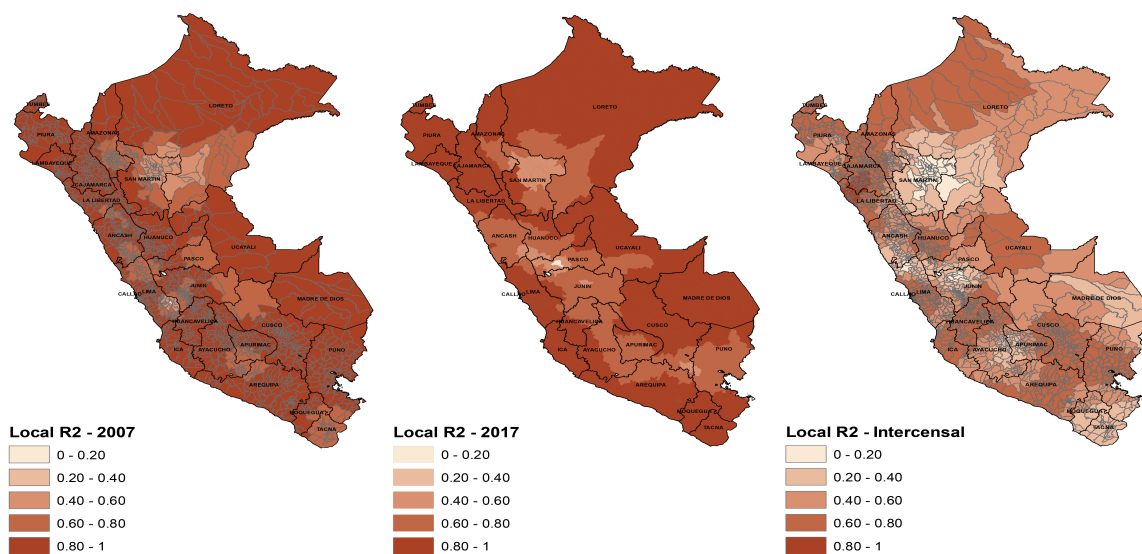
For 2007, the mean value of the effect of Female Head on poverty is negative and close to zero, -0.029, differing in sign from that obtained in the OLS; however, the distribution of the local effects is ambiguous, given that negative values are registered in the lower percentile and positive values in the upper percentile. This ambiguity is also present in the intercensal model; however, the mean value is positive, coinciding with that obtained in the OLS. In contrast to these results, for 2017, values are obtained with a more stable sign and in accordance with the OLS. That is, the mean value of Female Head on poverty is -0.317, likewise, its central local coefficients fluctuate on negative values ranging from -0.460 to -0.153.

One possible explanation for this effect is the role of mothers as direct recipients of the

cash transfer and the main responsible for the fulfillment of the co-responsibilities of the *Juntos* program, a program that benefits poor households whose members include children under 19 years of age and pregnant women. This program has been the subject of several studies showing favorable results on poverty reduction and an increase in the rate of health checkups for children under 5 years of age (Perova and Vakis, 2012; Escobal and Benites, 2012). Likewise, although the program emphasizes the welfare of children to stop intergenerational poverty, there is evidence that the program also generates benefits for women by fostering greater bargaining power, which would allow them to be more involved in decisions about household resources, enabling efficient household management (Alcázar and Espinoza, 2014).

Finally, regarding Altitude, positive mean values of 0.097, 0.045 and 0.108 are obtained for 2007, 2017 and intercensal, respectively, and whose values coincide with the sign resulting from the OLS. Likewise, the distribution of the central values are stable in sign for 2007 and 2017, registering differences in the intercensal case whose values fluctuate between negative and positive values, but the latter predominating. In addition, Table 3 shows that the adjusted  $R^2$  obtained with the GWR model for the years 2007, 2017, and intercensal increased by 19.6, 20.9, and 41.3 percentage points, compared to those obtained with OLS, which shows that the explanatory capacity of the dependent variable improves notably when applying the GWR model.

Figure 2 shows the distribution of the values of the adjusted  $R^2$  of the GWR models at the district level. Indeed, we observed that in the case of the 2007 census, the minimum local  $R^2$  value is 37.7% and the maximum is 99.3%. These values improve in the case of the 2017 census, where the minimum value is 53.3% and the maximum is 98.1%. However, in the intercensal case, the local goodness of fit is reduced to a minimum value of 13% and a maximum value of 87.7%. In fact, the years 2007 and 2017 show a higher concentration of high local  $R^2$  values, only 3 districts (Miraflores, Vitis and Alis in the province of Yauyos) register values below 40%



Notes: Own elaboration based on data used in the estimations.

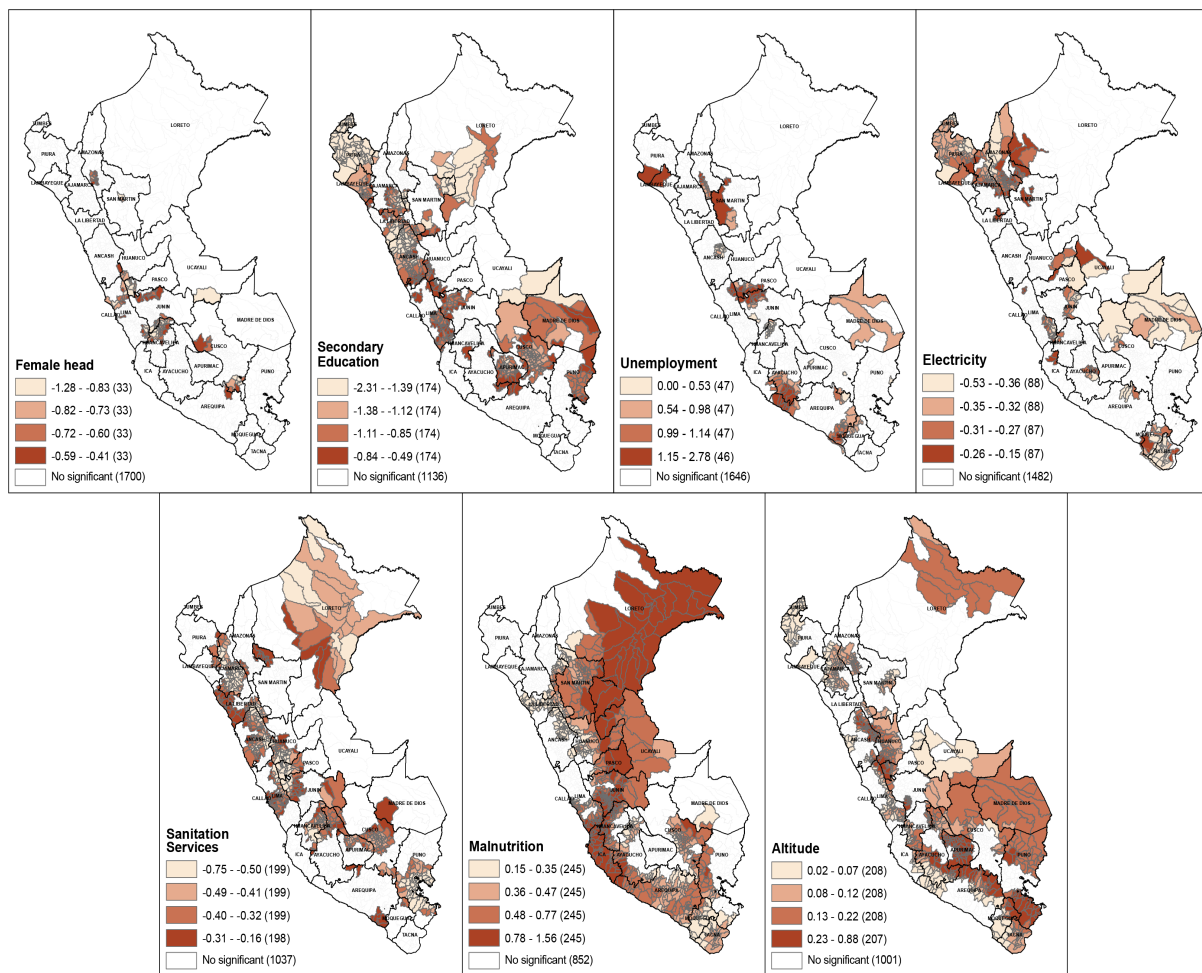
Figure 2. Local  $R^2$  of GWR.

(Quintile 2). While in the intercensal, little explanatory capacity is evidenced, mainly in districts in the Northeast of the San Martín region and north of the Junín region.

The present research shows the results of the three GWR models at 1% and 5% significance for each variable analyzed. Figures 3, 4 and 5 show the maps corresponding to the 2007 and 2017 census, and intercensal to visualize the spatial behavior of the local coefficients on monetary poverty in the districts of Peru. The maps only show the signs according to the predominant number of significant coefficients for each variable in line with the literature. Additionally, summary tables for each variable according to sign and significance level are shown.

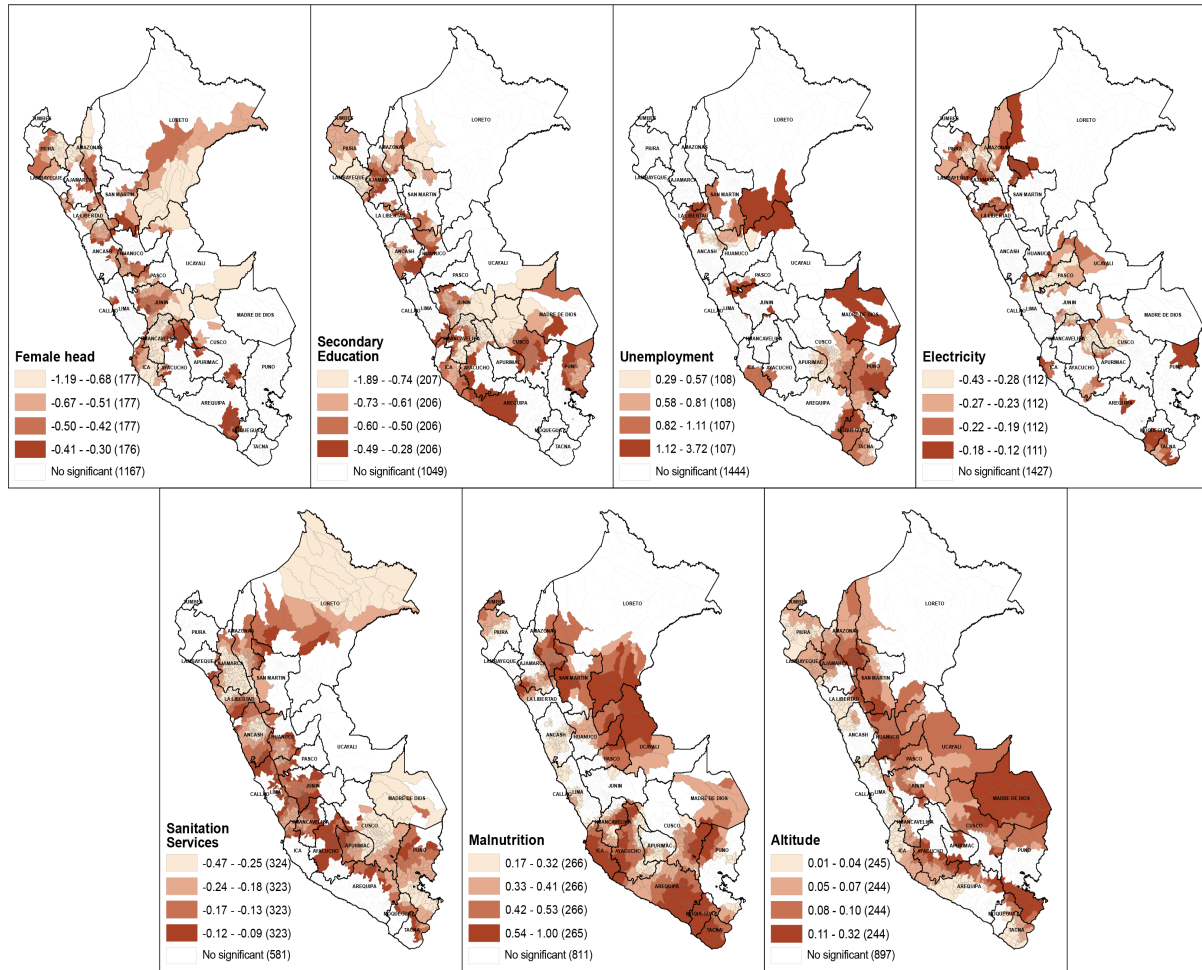
According to Tables 4 and 5, in the case of Female Head for 2007, significant coefficients are almost balanced in both signs, but predominantly in negative local values. Regarding spatial distribution, it is observed that the maximum negative and significant coefficients are concentrated in the districts of Huancavelica and Junín regions, expanding towards the central zone in the districts of Pasco, Huánuco and San Martín regions. However, for 2017, the results are more stable, whose local coefficients are concentrated in negative values, and the spatial distribution of the maximum values extends to the northwest, covering districts of Piura, Cajamarca, Amazonas and La Libertad; to the northeast in the districts of Loreto; and to the center-south in districts of Junín, Huancavelica, Cusco and Ica regions. For Secondary Education, the coefficients significant at 1% and 5% are predominantly negative with a total of 696 and 825 for 2007 and 2017, respectively. For 2007, it is highlighted that 100% and 98% of districts of the Tumbes and Piura regions register a greater effect negative and significant on the poverty rate. In addition, this effect is identified in the districts located on the border of La Libertad and Áncash; Loreto and San Martín; Ucayali and Madre de Dios regions. However, for 2017, this negative and significant effect is predominantly concentrated in the districts of southeastern regions of Peru. In addition, a displacement of this effect is observed in the districts of the regions highlighted in 2007.

The significant coefficients of Unemployment are mostly positive. For 2007, the maximum significant values are registered in 46 districts located, particularly, on the border of the regions of Piura and Lambayeque; Pasco, Junín and Lima; Arequipa and Ayacucho; as well as west of San Martín and south of Arequipa. For 2017, the maximum values move to the jungle region to districts of Loreto, Ucayali and Madre de Dios; to the highlands, to districts of Puno, Junín, Pasco and Cajamarca; to the coast, to districts of La Libertad, Lima, Arequipa and Moquegua. On the other hand, for 2007 and 2017, the value of the coefficients at 1% and 5% significance of the Electricity variable is predominantly negative on poverty. According to the 2007 results, the coefficients are concentrated in the northwest of Peru, particularly in 100% of districts of Tumbes and Piura regions. This effect is also concentrated in the center of the country, including districts of Pasco, Ucayali and Junín; additionally, coefficients of greater magnitude are registered in the southeast, specifically in 6 of the 11 districts of Madre de Dios, as well as in districts of southern regions such as Tacna and Moquegua. These results do not differ much from what was obtained for 2017; mainly, the changes are in Madre de Dios and Tumbes regions, where significant coefficients are no longer recorded; while an expansion of such coefficients is recorded in districts of Pasco, Ayacucho and Apurímac. Additionally, the local coefficients of the Sanitation Services variable are predominantly negative; this is evidenced by 795 and 1,293 significant coefficients



Notes: Own elaboration based on data used in the estimations.

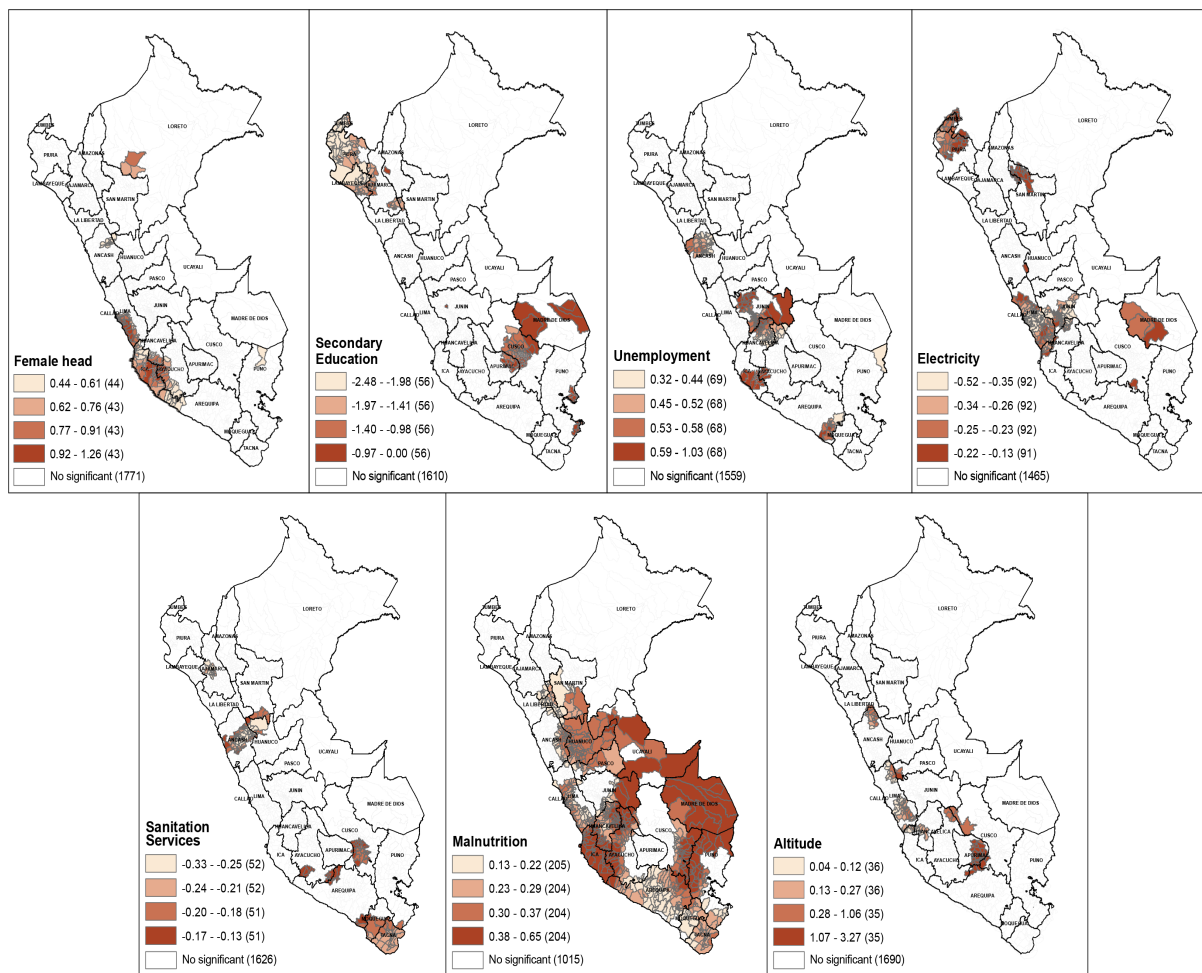
**Figure 3.** Maps of significant coefficients GWR - 2007.



Notes: Own elaboration based on INEL.

Figure 4. Maps of significant coefficients GWR - 2017.





Notes: Own elaboration based on INEL.

Figure 5. Maps of significant coefficients GWR - Intercensal.

for 2007 and 2017, respectively. For 2007, the spatial distribution of the significant coefficients is concentrated in districts in the Loreto region; then this effect shifts northwestward toward districts in Cajamarca. From there, it is concentrated in districts of the coastal regions (La Libertad, Áncash and Lima) and also includes districts of the central regions (Huánuco, Pasco, Junín) and districts of the southern highland regions (Huancavelica, Ayacucho, Apurímac, Cusco and Puno); particularly in the Puno region, 70% of its districts register negative and significant coefficients of sanitation services on poverty. For 2017, the distribution of the significant coefficients obtained in 2007 is reinforced and expanded, for example, it includes districts of Madre de Dios that register significant coefficients of greater magnitude on poverty.

**Table 4**

Summary of the significant coefficients of the GWR - Census 2007.

<b>Female Head</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	0.924	0.656	1.182	101	-0.825	-1.279	-0.530	69
5%	0.627	0.513	0.779	28	-0.615	-0.994	-0.409	63
Total	0.327	0.001	1.182	774	-0.289	-1.279	-0.001	1058
<b>Secondary Education</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	1.061	0.727	1.427	17	-1.340	-2.305	-0.560	492
5%	0.699	0.478	0.899	14	-0.806	-1.513	-0.488	204
Total	0.267	0.001	1.427	268	-0.736	-2.305	0	1564
<b>Unemployment</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	1.153	0.520	2.782	82	-2.605	-3.944	-1.646	8
5%	0.734	0.297	1.845	104	-1.665	-2.439	-0.786	16
Total	0.368	0	2.782	1179	-0.391	-3.944	-0.001	653
<b>Electricity</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	0.353	0.262	0.564	19	-0.346	-0.530	-0.197	227
5%	0.250	0.218	0.300	22	-0.272	-0.455	-0.154	123
Total	0.099	0.001	0.564	559	-0.164	-0.530	0	1273
<b>Sanitation services</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	0.426	0.373	0.491	4	-0.462	-0.752	-0.228	548
5%	0.350	0.335	0.365	2	-0.322	-0.569	-0.157	247
Total	0.095	0	0.491	237	-0.278	-0.752	0	1595
<b>Malnutrition</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	0.657	0.199	1.557	753	-0.421	-0.426	-0.417	2
5%	0.344	0.145	1.349	227	-0.362	-0.483	-0.217	31
Total	0.425	0.001	1.557	1568	-0.126	-0.483	0	264
<b>Ln(Altitude)</b>		<b>Positive</b>			<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs
1%	0.194	0.024	0.880	601	-0.112	-0.426	-0.055	24
5%	0.145	0.021	0.731	230	-0.204	-0.641	-0.041	7
Total	0.124	0	0.880	1590	-0.085	-0.642	0	242

Note: Own elaboration based on data used in the estimations.

**Table 5**

Summary of the significant coefficients of the GWR - Census 2017.

<b>Female Head</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.466	0.466	0.466	1	-0.665	-1.189	-0.393	401	
5%	0.406	0.325	0.509	4	-0.430	-0.757	-0.297	306	
Total	0.129	0.001	0.509	199	-0.371	-1.189	0	1675	
<b>Secondary Education</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.527	0.320	0.632	60	-0.734	-1.885	-0.381	464	
5%	0.324	0.261	0.509	17	-0.527	-1.843	-0.284	361	
Total	0.215	0.001	0.632	294	-0.466	-1.885	0	1580	
<b>Unemployment</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	1.145	0.418	3.719	249	-2.028	-2.213	-1.887	3	
5%	0.699	0.291	1.830	181	-1.718	-2.151	-1.163	17	
Total	0.514	0.001	3.719	1462	-0.378	-2.213	-0.001	412	
<b>Electricity</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.248	0.165	0.338	11	-0.273	-0.433	-0.168	207	
5%	0.199	0.138	0.243	15	-0.200	-0.316	-0.118	240	
Total	0.063	0	0.338	381	-0.132	-0.433	-0.001	1493	
<b>Sanitation services</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	-	-	-	-	-0.219	-0.470	-0.107	1,035	
5%	-	-	-	-	-0.122	-0.297	-0.088	258	
Total	0.024	0.001	0.087	47	-0.160	-0.470	-0.001	1,827	
<b>Malnutrition</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.481	0.229	0.995	791	-	-	-	-	
5%	0.301	0.167	0.475	272	-0.147	-0.166	-0.130	6	
Total	0.330	0	0.995	1,701	-0.051	-0.192	0	173	
<b>Ln(Altitude)</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.076	0.017	0.317	766	-0.072	-0.111	-0.049	18	
5%	0.069	0.013	0.262	211	-0.167	-0.448	-0.033	20	
Total	0.063	0	0.317	1582	-0.054	-0.448	0	292	

Note: Own elaboration based on data used in the estimations.

As can be seen in Tables 4 and 5, a total of 980 and 1,063 local coefficients of the variable Malnutrition are positive and significant for 2007 and 2017, respectively. In 2007, the significant values of quintile 5 are concentrated mainly in districts of the Loreto region; then they are located in San Martín and Ucayali regions, as well as in the central zone of Peru in the districts of Huánuco, Pasco, and Junín regions. Later, maximum positive values are registered in the southwest, encompassing the districts of Huancavelica, Lima, and, particularly, Ica region, where 95% of their districts register high values. In 2017, the magnitude of the coefficient increased in the districts of Tacna, Moquegua, and Arequipa regions. Besides new districts with significant coefficients in Madre de Dios, Tumbes, and Piura regions were registered; however,

**Table 6**

Summary of the significant coefficients of the GWR - Intercensal.

<b>Female Head</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.890	0.635	1.258	112	-0.738	-0.880	-0.662	4	
5%	0.569	0.438	0.889	61	-0.624	-0.924	-0.477	55	
Total	0.314	0.001	1.258	1079	-0.212	-0.924	-0.001	753	
<b>Secondary Education</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	1.066	0.695	1.349	52	-1.662	-2.477	-0.858	133	
5%	0.770	0.496	1.388	46	-1.138	-2.113	-0.539	89	
Total	0.343	0	1.388	983	-0.650	-2.477	0	849	
<b>Unemployment</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.614	0.464	1.029	71	-1.010	-1.426	-0.484	24	
5%	0.495	0.319	0.906	202	-1.136	-1.431	-0.474	51	
Total	0.295	0	1.029	1130	-0.356	-1.431	-0.001	702	
<b>Electricity</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.229	0.213	0.242	6	-0.324	-0.521	-0.195	227	
5%	0.171	0.133	0.235	52	-0.211	-0.296	-0.127	140	
Total	0.082	0	0.242	490	-0.134	-0.521	-0.001	1342	
<b>Sanitation services</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.236	0.157	0.310	68	-0.253	-0.311	-0.188	82	
5%	0.188	0.123	0.269	61	-0.194	-0.327	-0.132	124	
Total	0.088	0	0.310	842	-0.101	-0.327	0	990	
<b>Malnutrition</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.345	0.175	0.651	603	-0.342	-0.496	-0.218	97	
5%	0.213	0.134	0.453	214	-0.207	-0.436	-0.142	87	
Total	0.235	0.001	0.651	1311	-0.163	-0.496	0	521	
<b>Ln(Altitude)</b>		<b>Positive</b>				<b>Negative</b>			
Significance	Mean	Min	Max	Obs	Mean	Min	Max	Obs	
1%	0.749	0.063	3.267	73	-	-	-	-	
5%	0.555	0.044	2.141	69	-0.785	-2.115	-0.104	36	
Total	0.279	0	3.267	1251	0.258	-2.115	0	581	

Note: Own elaboration based on data used in the estimations.

the Junín and Loreto regions no longer have significant in large proportion as in 2007. Regarding the distribution of the local values of the Altitude variable, a greater number of positive and significant coefficients are observed for both years analyzed. For 2007, the high values of the significant coefficients are concentrated in the districts in the south of the country, as well as in districts in the center, which includes the regions of Huánuco, Áncash and Pasco. In the case of 2017, the number of districts with significant coefficients increased by 146 distributed, mainly, in the north (Amazonas); center (San Martín, Huánuco, Pasco, Junín and Ucayali); and southeast (Cusco, Madre de Dios and Puno).

Table 6 summarizes the results of the intercensal model. In the case of Female Head, there is a higher concentration of positive and significant coefficients; these significant coefficients are located, specifically, in the districts of Lima and in the border districts between the regions of Ica, Ayacucho and Huancavelica. However, this result is contrary to what was obtained in 2017, whose result indicates that the border districts of those regions register the maximum negative and significant values of Female Head on poverty. Regarding the other variables, a similar behavior to what was obtained in 2007 and 2017 is observed in the signs of the coefficients of the intercensal model; but there are differences in the spatial distribution. However, it is important to note that the estimates obtained from the intercensal model do not conform to what was expected in the face of both anomalous results in the spatial distribution and low explanatory capacity, as shown above with the adjusted  $R^2$ .

## 6. Conclusions

In Peru, the literature has mainly focused on poverty analysis at an aggregate level. Therefore, the main contribution of this research is to conduct the analysis at the local level, that is, to analyze the factors that explain the spatial heterogeneity of monetary poverty in each district of the Peruvian territory.

The methodology used in this study is based on the Geographically Weighted Regression model, which allows us to capture the non-stationary spatial component of poverty in the districts. Unlike a global regression model, this approach makes it possible to obtain estimators for each territorial administration and to formulate policies that help identify the districts whose factors associated with poverty are lagging behind. Likewise, the application of the GWR model shows a notable improvement in the explanatory capacity with respect to that obtained with the OLS model. Likewise, it should be noted that a Monte Carlo simulation was run, from which it was determined that all the coefficients are locally variable variables affected by the local context, which allows us to register a heterogeneous impact on poverty.

The results of this research allow us to identify districts with significant local coefficients. In general, the estimates show that the increase in secondary education, electricity, sanitation services and female headship have an effect on poverty reduction at the local level. For 2007, these significant effects are mainly concentrated in the districts of the province of Daniel Alcides Carrión and Pasco in Pasco region; in Huarochirí, Oyón and Yauyos in Lima region; and in Celendín, Chota and San Ignacio in Cajamarca region. For 2017, the results show a shift towards districts in the province of Chupaca, Concepción, Huancayo in Junín region; in Huancavelica and Tayacaja in Huancavelica region; and in Jaen, San Marcos in Cajamarca region.

On the contrary, an increase in unemployment, malnutrition and altitude do not contribute to poverty reduction. For 2007, these significant effects predominate in the districts of the province of Mariscal Luzuriaga, Carlos Fermin Fitzcarrald in Áncash region; in Caravelí, Caylloma in Arequipa region; and in Lucanas and Parinacochas in Ayacucho region. For 2017, this effect is reinforced in the south in districts of the provinces of Canchis, Quispicanchi, Paucartambo, Canas and Calca in Cusco region; in Candarave, Jorge Basadre, Tacna and Tarata in Tacna region; and in Huaylas, Huari and Antonio Raymondi in Áncash region.

From the results, the existence of heterogeneous spatial dynamics on poverty at the district level is clearly evidenced. This allows us to visualize in which districts, for example, educational policies are succeeding in combating poverty, practices that could be scaled up to the national level. However, we can also visualize those districts where the relationship is not favorable in poverty reduction; therefore, the focus of territorial policy should concentrate on these territories. The possibility of identifying the least favored districts rigorously and accurately promotes a new public management model that allows the design of policies based on the particular conditions of each territory, thus achieving more efficiency and equity in regional development.

Based on the above-mentioned empirical results, the highlighted policy implications are as follows: (1) establish strategies to attract public and private investments in intermediate cities that allow for a fluid economic dynamic; (2) rural poverty should be further explored at the district level because it is where the highest poverty rates have been evidenced; therefore, one of the policy proposals is the construction of functional territories, with the purpose of articulating the territories as an agricultural labor market or other sectors that contribute to community development develops; (3) promote the development of productive infrastructure for the creation of appropriate conditions for the development of the endogenous potential of the district space; (4) allocate budget to subnational governments with higher poverty rates that have strategies focused on implementing, for example, educational policies or access to basic services such as electricity, sanitation and water to the poorest households, conditioned to efficient budget execution.

Finally, we would like to acknowledge the main limitations in this study. First, there are different methods to measure poverty. Although at present the multidimensional approach predominates, the official and accepted measure for Peru is monetary poverty. Second, we have observed an increase from 1,832 to 1,874 districts between the period 2007 and 2017. In this regard, the intercensal model only considers districts found in both censuses, which means that 42 districts created around 2017 are not considered. Third, a convergence problem has been observed with the semiparametric estimation approach (non-invertible Hessian) as more variables were introduced to the GWR model. For that reason, we decide to limit the number of variables, based on a multicollinearity analysis (VIF) test to exclude highly correlated variables. Finally, it is worth mentioning that this paper focuses on the role of observed spatial heterogeneity and that causality remains a topic for future research.

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